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# UNSUPERVISED LEARNING BASED INTERACTION FORCE MODEL FOR NONSPHERICAL PARTICLES IN INCOMPRESSIBLE FLOWS

FE0031905

Soohwan Hwang, Liang-Shih Fan (PI)

# Outline

- Project Description and Objectives
- Project Update
- Preparing Project for the Next Steps
- Concluding Remarks

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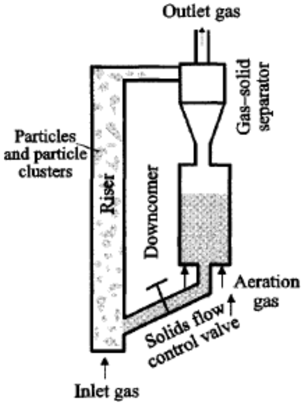
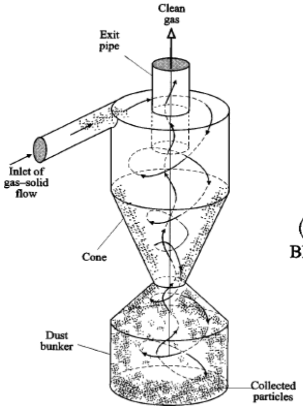
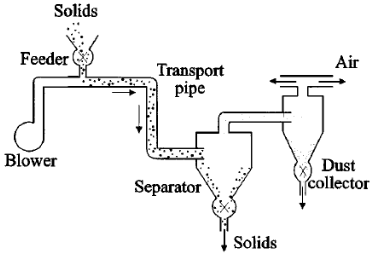
# Project Description and Objectives

## Gas-Solid system

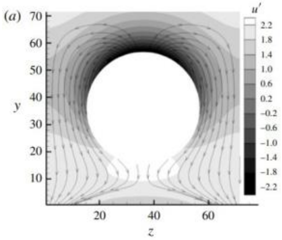


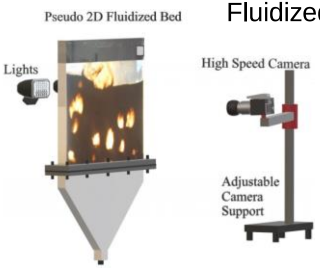




## Interaction forces

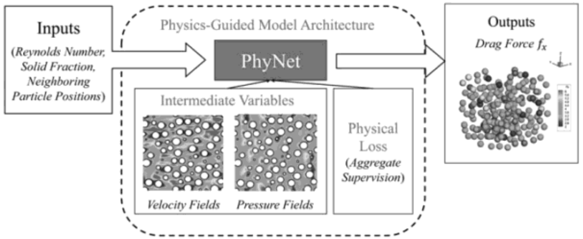
DNS



Fluidized bed




Machine Learning




Liang-Shih Fan, Principles of gas-solid flows (1999)

Qiang Zhou et al., Journal of Fluid Mechanics, 765 (2015)

Cesar Martin Venier et al. International Journal of Numerical Methods for Heat and Fluid Flow (2019)

Long He et al., Powder Technology 345 (2019)

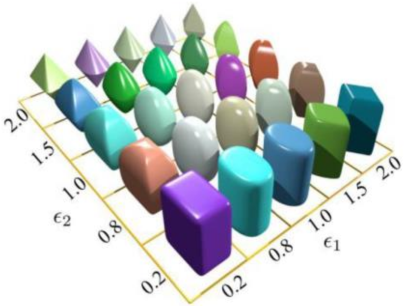
# Project Description and Objectives

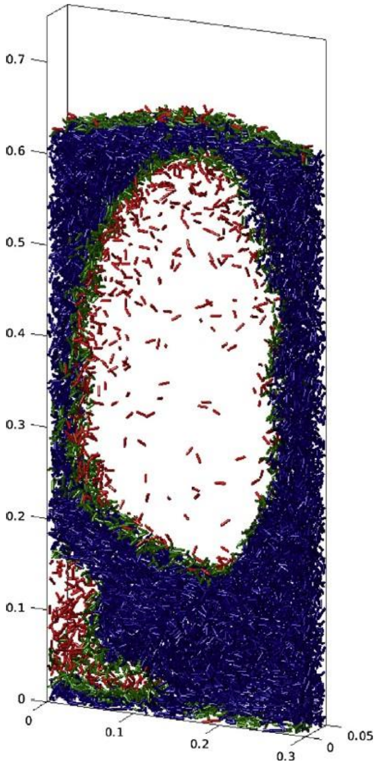
## Non-spherical particle

- Difficult to define the geometrical factors sphericity, flatness, elongation and circularity, etc.
- Data for the interaction force between non-spherical particles and the fluids are limited.
- Correlation may be highly-nonlinearity.

## Objectives

- Developing a neural network-based force model for a diversity of non-spherical particles.
- From low O(1) to moderate O(100) Reynolds number.
- From low to high volume fraction.




Shiwei Zhao et al., Int J Numer Anal Methods Geomech., 43 (2019)

Vinay V. Mahajan et al., Chemical Engineering Science, 192 (2018)

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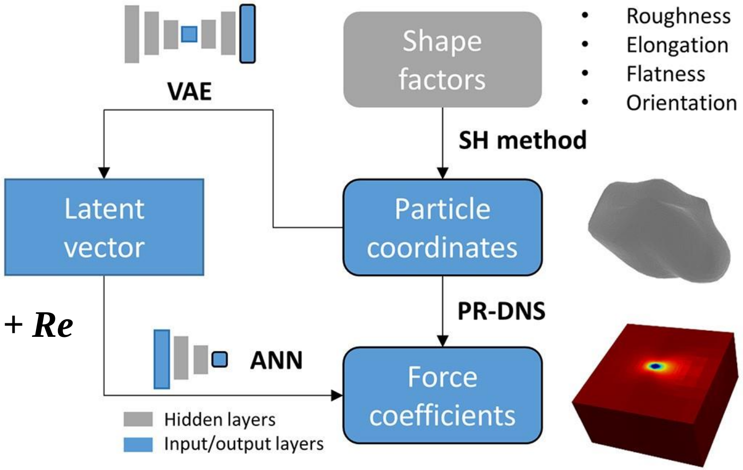
# Project Update

| Tasks | Year 1 | | | | Year 2 | | | | Year 3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 10/20 | 1/21 | 4/21 | 7/21 | 10/21 | 1/22 | 4/22 | 7/22 | 10/22 | 1/23 | 4/23 | 7/23 |
| PR-DNS development | | | | | | | | | | | | |
| Particles Generation & VAE | | | | | | | | | | | | |
| Low Re data Collection | | | | | | | | | | | | |
| High Re data Collection | | | | | | | | | | | | |
| MLP Training | | | | | | | | | | | | |

Current stage

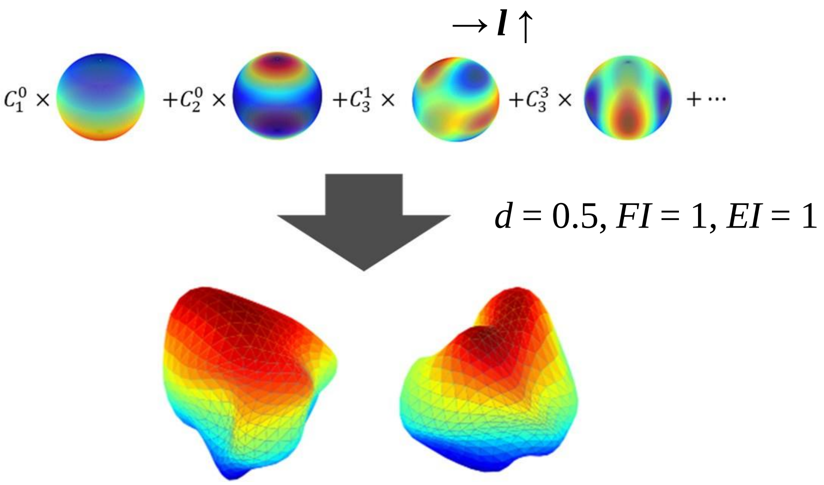
Preliminary Results

## Strategy




ANN : Artificial Neural Network
PR-DNS : Particle Resolved Direct Numerical Simulation

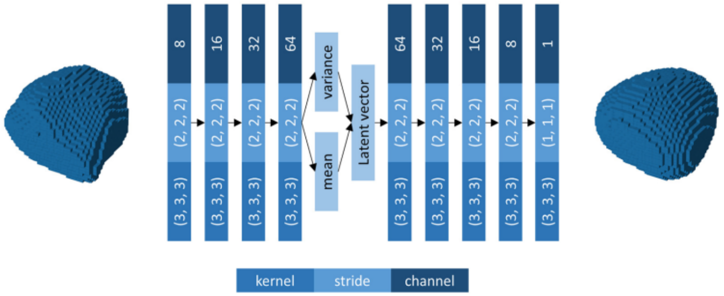
## Spherical Harmonic (SH) Methods




The SH method includes random numbers so the outputs have different shapes

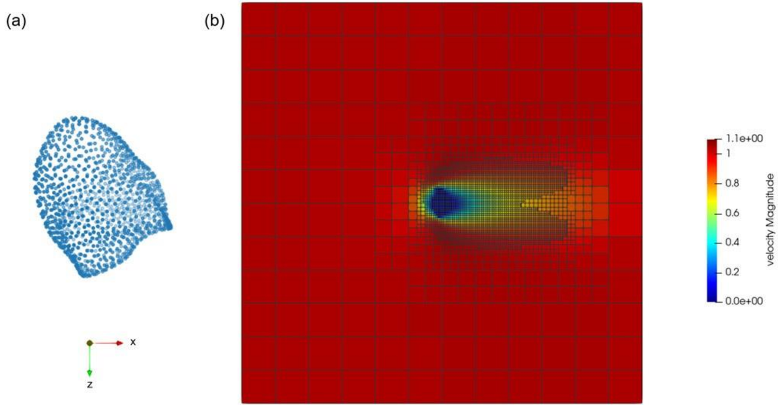
## VAE

- Deep CNN layers with ELUs
- 2,000 data to train, 400 data to validate, 10400 data for DNS
- Less than 1% reconstruction error




## PR-DNS Development

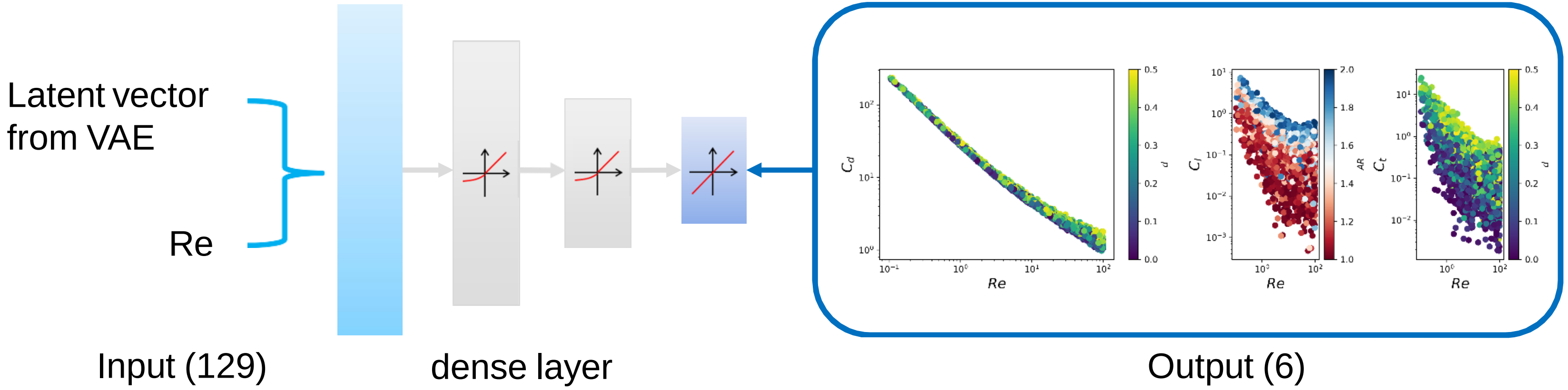
- Simplified Spheric Gas Kinetic Scheme (GKS)
- Immersed boundary Method (IBM) / Direct Forcing
- Adaptive Mesh Refinement (AMR)



# PR-DNS Results / ANN 1

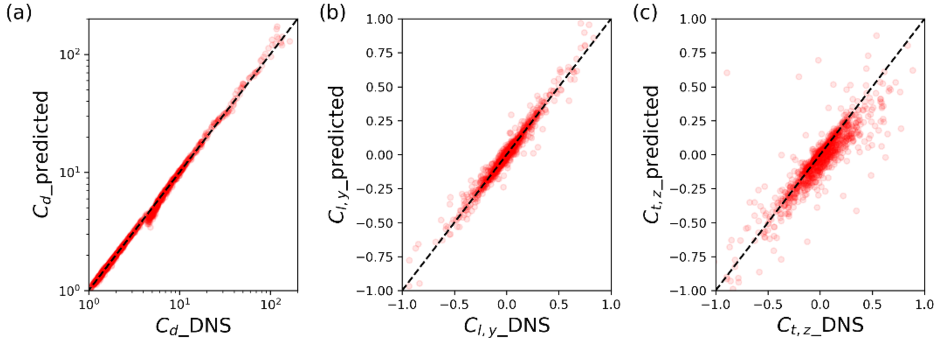
- Re = 0.1~100, 10400 single particles
- Two fully connected hidden layers with 32 and 8 nodes with ELUs, and an output layer with linear function

$$C_f = \frac{-\sum_l F_l \Delta V_l}{\frac{1}{2}\rho \boldsymbol{u}_\infty{}^2 (\frac{Deq}{2})^2 \pi}, \quad C_t = \frac{-\sum_l \boldsymbol{r}\times F_l \Delta V_l}{\frac{1}{2}\rho \boldsymbol{u}_\infty{}^2 (\frac{Deq}{2})^3 \pi}$$



# ANN 1 results

- MSEs of ANN 1 for evaluation data are:
  - $C_d$ : 7.97
  - $C_l$ : 0.00546
  - $C_t$ : 0.0647
- MAPE of $C_d$ is 3.3%

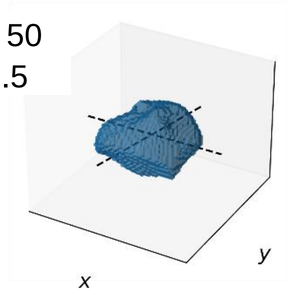


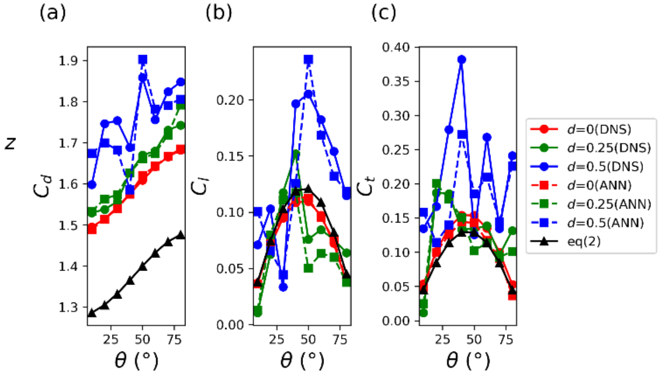

$$C_d = \frac{a_1}{Re^{a_2}} + \frac{a_3}{Re^{a_4}} + \left(\frac{a_5}{Re^{a_6}} + \frac{a_7}{Re^{a_8}} - \frac{a_1}{Re^{a_2}} - \frac{a_3}{Re^{a_4}}\right) sin(\theta)^{a_9}$$

$$C_l = \left(\frac{b_1}{Re^{b_2}} + \frac{b_3}{Re^{b_4}}\right) sin(\theta)^{b_5 + b_6 Re^{b_7}} cos(\theta)^{b_8 + b_9 Re^{b_{10}}}$$

$$C_t = \left(\frac{c_1}{Re^{c_2}} + \frac{c_3}{Re^{c_4}}\right) sin(\theta)^{c_5 + c_6 Re^{c_7}} cos(\theta)^{c_8 + c_9 Re^{c_{10}}}$$

*Re* = 50
*d* = 0.5

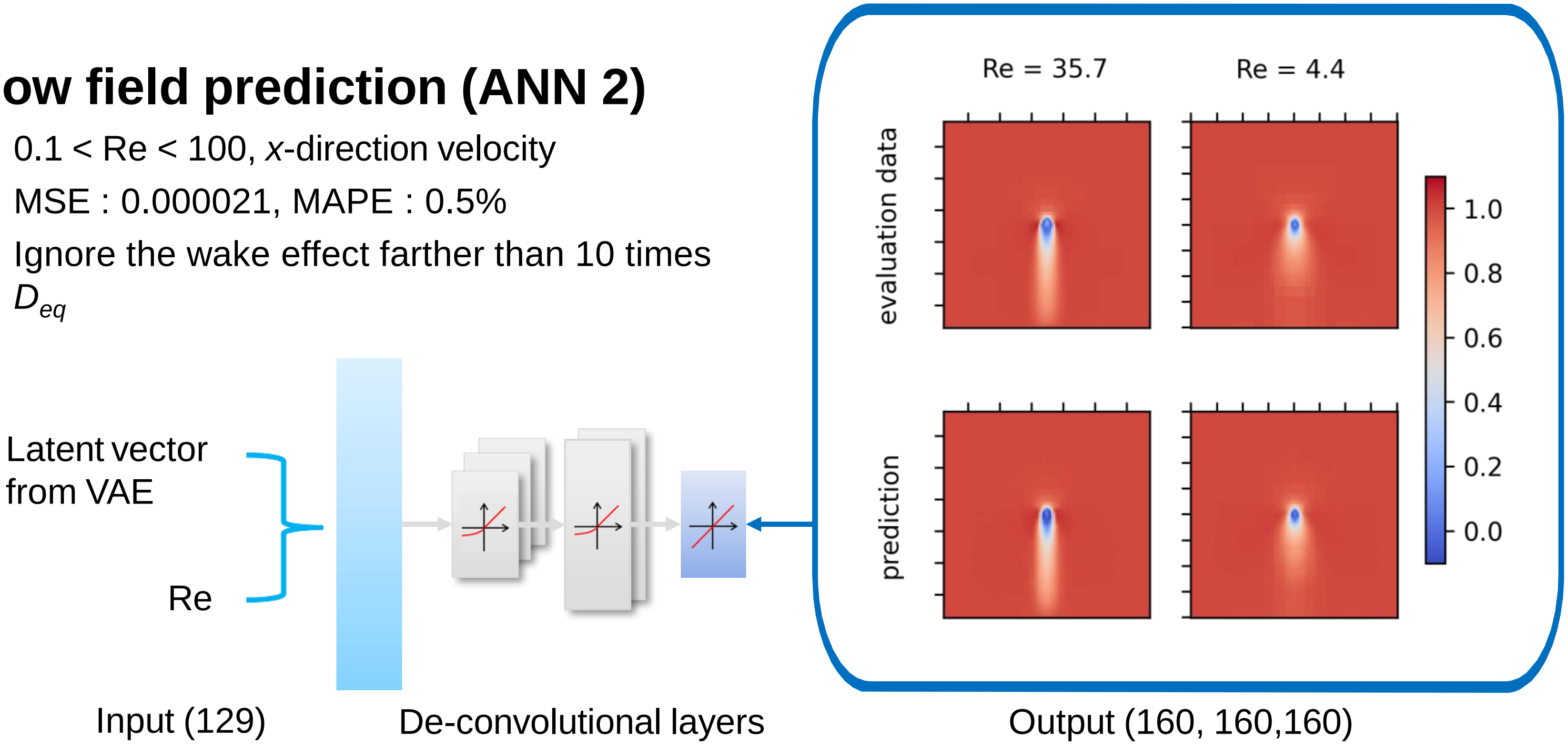


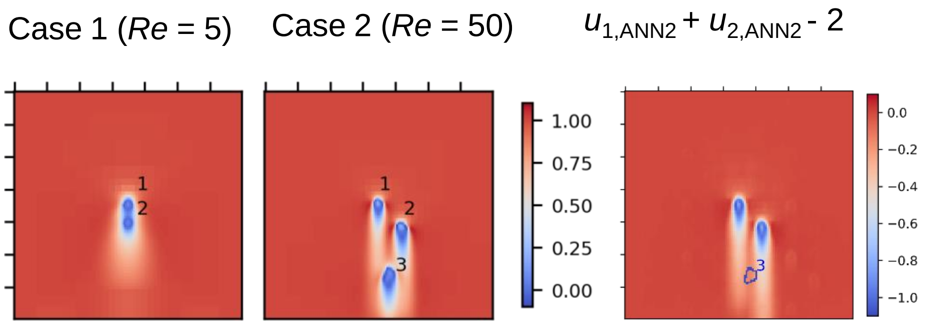

M. Zastawny, el al., International Journal of Multiphase Flow. 39 (2012)

# Flow field prediction (ANN 2)

- 0.1 < Re < 100, *x*-direction velocity
- MSE : 0.000021, MAPE : 0.5%
- Ignore the wake effect farther than 10 times $D_{eq}$



# PIEP with ANN 1 and ANN 2




$$\tilde{F}_{drag,i} = \bar{F}_{drag}(Re_i,\varphi) + \left\{3\pi\mu d_i \sum_{\substack{j=1\\ j\neq i}}^{N} \overline{u_{j\to i}}^{S}\left(1+0.15{Re_i}^{0.687}\right)\right\}$$

velocity perturbation due to *j* th neighbor

$$\tilde{C}_{D,i} = C_D(Re_i)\left\{f(\varphi,Re_i) + \frac{\sum_{\substack{j=1\\ j\neq i}}^{N}\overline{u_{j\to i}}^{S}}{u_{mac}}\right\}$$

ANN 1 ($C_D(Re_i)$)

ANN 2 ($\sum_{j=1, j\neq i}^{N}\overline{u_{j\to i}}^{S}$)

| $C_D$ / error | Case 1 | | Case 2 | | |
|---|---|---|---|---|---|
| | 1 | 2 | 1 | 2 | 3 |
| DNS (multi-particle) | 6.66 | 4.48 | 1.73 | 1.68 | 1.40 |
| DNS (single particle) | 7.48 | 7.21 | 1.75 | 1.71 | 1.63 |
| ANN 1 | 7.53/ 13.1% | 7.37/ 64.5% | 1.75/ 1.11% | 1.71/ 2.3% | 1.62/ 16.3% |
| ANN 1+ ANN 2/PIEP | 6.74/ 1.2% | 4.24/ 5.2% | 1.73/ 0.1% | 1.71/ 2.1% | 1.37/ 1.6% |

PIEP : pairwise-interaction extended point-particle, G. Akiki et al., Journal of Computational Physics (2017)

# Preparing Project for Next Steps

## Market Benefits/Assessment

MFiX only provides the drag force model for spherical particles

Industrial CFD application requires the comprehensive interaction force model

## Technology-to-Market Path

This project will provide the interaction force model including lifting force and torque which can be implemented in MFiX

Multi-particle system will be studied to predict the interactive force for more dense system.

# Concluding Remarks

- This study provides the interaction force model for the irregular shaped particle which is practical in industry.
- In MFiX-DEM, the NN based model can be implemented to obtain the interaction forces.
- The neighboring effect will be included in the future work for the dense multi-particle system.

# Acknowledgement

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